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# **Assessing FPAR Source and Parameter Optimization Scheme in Application of a Diagnostic Carbon Flux Model**

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## Abstract

The combination of satellite remote sensing and carbon cycle models provides an opportunity for regional to global scale monitoring of terrestrial gross primary production, ecosystem respiration, and net ecosystem production. FPAR (the fraction of photosynthetically active radiation absorbed by the plant canopy) is a critical input to diagnostic models, however little is known about the relative effectiveness of FPAR products from different satellite sensors nor about the sensitivity of flux estimates to different parameterization approaches. In this study, we used multiyear observations of carbon flux at four eddy covariance flux tower sites within the conifer biome to evaluate these factors. FPAR products from the MODIS and SeaWiFS sensors, and the effects of single site vs. cross-site parameter optimization were tested with the CFLUX model. The SeaWiFS FPAR product showed greater dynamic range across sites and resulted in slightly reduced flux estimation errors relative to the MODIS product when using cross-site optimization. With site-specific parameter optimization, the flux model was effective in capturing seasonal and interannual variation in the carbon fluxes at these sites. The cross-site prediction errors were lower when using parameters from a cross-site optimization compared to parameter sets from optimization at single sites. These results support the practice of multisite optimization within a biome for parameterization of diagnostic carbon flux models.

## Introduction

The ability to monitor terrestrial carbon fluxes at regional to global scales is of increasing interest in relation to understanding unmanaged and managed influences of the biosphere on the global carbon cycle (Cannadel et al. 2007). Satellite remote sensing potentially offers spatially continuous information on relevant land surface properties including land cover, vegetation type, vegetation structure, disturbance history, phenology, drought stress, and light use efficiency (Running et al. 1999, Turner et al. 2004). However, design of appropriate models that use this information for scaling carbon fluxes, and parameterizing these models for spatial mode application, remain significant research issues.

In diagnostic carbon cycles models, i.e. driven by time series data from satellites on vegetation greenness, canopy gross primary production (GPP) is generally estimated as the product of APAR (the absorbed photosynthetically active radiation) and light use efficiency (LaFont et al. 2002, Mahadevan et al. 2008). Scalars for environmental stress factors like low temperature and high vapor pressure deficit may be used to modify a base rate for light use efficiency (LUE). Autotrophic respiration is often calculated as a fixed proportion on GPP. Algorithms for heterotrophic respiration are more variable, with some using simple base rate formulations and others using multiple litter and soil carbon pools with varying turnover times.

FPAR (the fraction of incoming PAR absorbed by the canopy) is a critical input to diagnostic models and global FPAR products are now derived from multiple sensors (MODIS, Myneni et al. 2002; SeaWiFS, Gobron et al. 2006; MERIS, Gobron et al.

2008). The algorithms generally use empirical relationships or radiation transfer models). Ground validation of these FPAR products has been limited to a few tens of sites at most (e.g. Fensholt et al. 2006, Turner et al. 2006a) and accuracy varies widely.

Diagnostic models tend to be kept simple enough that the parameters can be optimized from measurements. The need for parameter optimization traces in part to the limitations in satellite data, notably effects of cloudiness on FPAR (the fraction of incident PAR absorbed by the canopy). To some degree, parameter optimization compensates for possible errors elsewhere in the combination of model structure and model inputs (Medlyn et al. 2005).

In the simplest case, a diagnostic model has been optimized across all biome types using a single set of measurements of net primary production (NPP) as reference values (Potter et al. 1993). More commonly, diagnostic models are parameterized at the biome level of vegetation stratification, the rationale being that in the case of vegetation parameters like LUE, plants make evolutionary trade-offs such that specialization for one habitat will make it less competitive in other climate regimes. For parameters related to heterotrophic respiration ( $R_h$ ), the situation is similar in that controls on decomposition rate, such as litter quality, may be characteristic of specific ecosystem types (Adair et al. 2008).

Because GPP and ecosystem respiration ( $R_e$ ) can be estimated from measurements of net ecosystem exchange (NEE) at eddy covariance flux towers (Densai et al. 2008), establishment of a network of tower sites (Baldocchi et al. 2001) has greatly enhanced the possibilities for parameterizing and testing diagnostic models (e.g. Mahadevan et al. 2008). However, there has been little study of using multiple flux tower sites for parameterization within a single biome. Makela et al. (2008) found that responses of GPP to environmental stressors were similar across 5 conifer sites but base rates for LUE were different.

In this study, we evaluate alternative FPAR sources and parameter optimization schemes for a carbon cycle diagnostic model applied at four sites in western North America dominated by conifer forests. Three years of tower data at each tower site provided the reference observations. Independent optimizations were performed at each tower site and pooled across sites with each of 3 forms of FPAR.

## Methods

### Sites

Four coniferous forest sites in western North America were used in the study (Table 1). Each had a multiyear record of eddy covariance flux measurements and observations of meteorological variables. The sites varied widely in climate conditions, stand age, and leaf area index. The Campbell River site (CR) is a young Douglas-fir (*Pseudotsuga menzeisii*) stand that originated with a clear-cut harvest in 1949. The stand is located on Vancouver Island in western Canada and the climate is characterized by cool, wet winters and mild dry summers. The Wind River site (WR) is an old-growth stand in the western

Washington (USA) dominated by Douglas-fir and western hemlock (*Tsuga heterophylla*). Winters are colder and summers warmer than at CR. The Metolius River site (MR) is a mature ponderosa pine (*Pinus ponderosa*) stand in central Oregon (USA) that was harvested around 1920. Winters are cold and summers dry, with relatively high summer vapor pressure deficits (VPDs). The Niwot Ridge site in central Colorado (USA) was logged about 100 year ago. It is a subalpine forest dominated by Engelmann spruce (*Picea engelmannii*), subalpine fir (*Abies lasiocarpa*), and lodgepole pine (*Pinus flexilis*).

Methodology for measurement of meteorological variables and NEE at the sites are given in the references in Table 1. Missing meteorological data were filled from nearby meteorological station data and gaps in flux observations were filled by reference to empirical functions driven by meteorological data derived from periods of good quality observations. GPP estimates were derived as the inverse of net ecosystem exchange (NEE) minus ecosystem respiration ( $R_e$ ) during daytime periods, with  $R_e$  based on relationships of nighttime NEE to air or soil temperature. At NR, the reference flux values were the best fit estimates from the SIPNET model fit to the NEE observations (Sachs et al. 2007). GPPs from SIPNET were of similar magnitude to GPPs modeled using the temperature/nighttime NEE approach (Sims et al. 2008).

## Model Description

A diagnostic carbon flux model (CFLUX) developed previously for application in coniferous forests was used in this study. The detailed algorithms and their rationales are given in Turner et al. (2006) and briefly described here. The model produces daily estimates of GPP, autotrophic respiration ( $R_a$ ), heterotrophic respiration ( $R_h$ ), and NEE. Daily meteorological inputs are photosynthetically active radiation, 24 hr minimum temperature, 24 hr average temperature, daytime mean vapor pressure deficit (VPD), and 24 hr total precipitation. Site variables are vegetation type, stand age, and soil water holding capacity (here we used 200 mm in all cases).

The GPP estimate is based on a light use efficiency approach.

$$\text{GPP} = e_g * \downarrow\text{PAR} * \text{FPAR} \quad (1)$$

Where

GPP = gross primary production ( $\text{gC m}^{-2} \text{d}^{-1}$ )

$e_g$  = final LUE ( $\text{gC MJ}^{-1}$ )

$\downarrow\text{PAR}$  = incident photosynthetically active radiation ( $\text{MJ m}^{-2} \text{d}^{-1}$ )

FPAR = fraction of  $\downarrow\text{PAR}$  absorbed by the canopy.

$e_g$  is calculated from a minimum value (based on observations at the flux tower of clear sky LUE under favorable metrological conditions) that is adjusted upward as a function of cloudiness and downward as a function of  $T_{min}$ , VPD, the soil water status (SW), and the stand age (SA).

$R_a$  is the sum of maintenance respiration ( $R_m$ ) and growth respiration ( $R_g$ ).

$$R_m = R_{m-base} * Q_{10}^{((T_{air} - 20)/10)} * (1/k) (\log (1-FPAR)) \quad (3)$$

where

$R_{m-base}$  = base rate of autotrophic respiration ( $gC\ m^{-2}\ d^{-1}$ )

$Q_{10}$  = change in rate for a  $10^\circ C$  increase in temperature (here we use 2.0)

$T_{air}$  = daily (24 hr) mean air temperature

$k$  = radiation extinction coefficient (here we use 0.5)

FPAR = fraction of  $\downarrow PAR$  absorbed by the canopy.

The  $R_g$  component of  $R_a$  is calculated on a daily basis as:

$$R_g = (GPP - R_m) * R_{g\_frac}$$

Where

$R_{g\_frac}$  is the fraction of carbon available for growth that is used for growth respiration (here we used 0.25).

The  $R_h$  algorithm also uses a base rate, and contains functions for sensitivity to temperature, soil moisture, and stand age.

$$R_h = R_{h-base} * S_{ST} * S_{SW} * S_{SA} * FPAR \quad (6)$$

Where

$R_{h\text{-base}}$  = base rate of heterotrophic respiration ( $\text{gC m}^{-2} \text{d}^{-1}$ )

$S_{ST}$  = scalar for soil temperature

$S_{SWh}$  = scalar for soil water content

$S_{SAh}$  = stand age factor

FPAR = fraction of  $\downarrow\text{PAR}$  absorbed by the canopy

CFLUX calculates a simple water balance based on precipitation as the input and evapotranspiration (ET) plus runoff as outputs. ET is calculated from GPP and water use efficiency ( $\text{mm gC}^{-1}$ ).

### **FPAR Data**

We obtained 3 years of the standard FPAR product (collection 4.5) from the MODIS sensor for each site from the U.S.G.S. Data Archive and Analysis Center (LPDAAC 2008). The standard FPAR product ( $\text{MODIS}_{\text{orig}}$ ) has a spatial resolution of 1 km and is an 8-day maximum value (Myneni et al. 2002). The value is derived from a radiation transfer algorithm when possible and an empirical spectral vegetation index approach as a backup algorithm. Quality flags give an indication of which algorithm was used and the relative quality of the estimate (Cohen et al. 2006).

To minimize errors associated with low quality data, a simple linear interpolation algorithm was used to fill values for days with a low data quality flag ( $\text{MODIS}_{\text{fill}}$ ) (Zhao et al. 2005) and we applied it to the  $\text{MODIS}_{\text{orig}}$  data to form a  $\text{MODIS}_{\text{fill}}$  product. We also investigated the effect of a third form of FPAR in which the  $\text{FPAR}_{\text{fill}}$  version is smoothed with the TIMESAT algorithm (Jonsson and Eklund 2004). This version ( $\text{MODIS}_{\text{TS}}$ ) was produced by NASA over North America for evaluation purposes (Gao et al. 2007, Nightengale et al. In Press).

We also tested an independent FPAR data set for these sites derived from the SeaWiFS sensor (Gobron et al. 2006). Spatial resolution of SeaWiFS data is  $\sim 2.2$  km and temporal resolution is 10 days. As with the MODIS FPAR product, we used the Zhao et al. (2005) algorithm to fill missing data ( $\text{SW}_{\text{fill}}$ ).

### **Parameter Optimization Approach**

The scheme for optimizing CFLUX parameters at a single flux tower sites and year is described in Turner et al. (2006). Briefly, there are three steps. The reference data required are daily estimates for GPP and NEE, and an estimate of NPP at the site. Here we used tower-based GPP and NEE. NPP was assumed to be a fixed proportion of GPP based on measurements at the site (WR, CR, MR) or 0.47 following Waring et al. (1998). The possible range for the parameter values is based on literature studies and preliminary



model runs. The optimization may also choose to not use the temperature or VPD scalars if error is minimized by doing so. All combinations over the complete possible range of each parameter are examined. In the first step, the five parameters controlling GPP (maximum LUE and the upper and lower bounds for the VPD and  $T_{min}$  effects) are optimized using tower GPP for reference values. Minimum Root Mean Square Error (RMSE) is used as the criteria for selecting the optimum parameter set. In the second step, the optimized GPP parameters are carried over and the base rate for maintenance respiration ( $R_{m-base}$ ) is optimized using the annual NPP as a reference and the minimum bias as the selection criteria. Lastly, the optimized parameters for GPP and  $R_m$  are carried over and the base rate for  $R_h$ , along with a parameter that determines sensitivity to temperature, and the minimum FPAR (permits  $R_h$  when FPAR is artifactually low (Turner et al. 2006), are optimized using the daily (24 hr) NEEs as the reference values, and the minimum RMSE as the selection criteria.

To extend the optimization procedure to cover a three year interval for a site, a single RMSE was computed for the 3 years of data ( $n = 1095$ ) in the GPP and NEE comparisons and the 3 year sum of the absolute values for the NPP bias was used in the  $R_{m-base}$  optimization. Similarly, to optimize parameters over multiple sites and years, single RMSEs and sums of absolute NPP bias were employed. All parameters except those optimized and  $LUE_{clear-sky}$  were the same in the cross-site optimization. Site level  $LUE_{clear-sky}$  was retained because it was assumed that in a spatial model application it could be retrieved from remote sensing (Drolet et al. 2008).

A cross-site optimization was performed for each FPAR type then a site-level optimization was performed for each site and FPAR type. For comparisons of site-level and cross-site optimizations within one FPAR type, results are presented for the case with  $SW_{fill}$  FPAR because that FPAR type yielded the lowest RMSE for NEE in the initial FPAR comparison.

## Results

### FPAR Comparisons

In the  $MODIS_{orig}$  FPAR product, there were multiple 8-day periods at all sites when high quality data were not available, probably because of persistent heavy cloud cover (Figure 2). The original data from the SeaWiFS FPAR product showed a similar pattern. These periods of no data occurred during all seasons but were most prevalent in winter. The simple gap filling algorithm of Zhao et al. (2005) effectively corrected most of these problems. At CR, which does not usually experience winter snow cover, there were still some artifactual periods of low  $MODIS_{fill}$  FPAR in winter. At WR and MR, there is occasional snow cover in the winter but the  $MODIS_{fill}$  FPAR had no major artifacts. At NR, there is a solid snow cover all winter, which would cover some of the tree vegetation, hence the strong season signal in  $MODIS_{fill}$  FPAR at NR is reasonable.

In terms of the maximum FPAR, there was remarkable little difference in  $MODIS_{fill}$  among these sites considering the great range of LAI. Summer maximum  $MODIS_{fill}$  was

close to 0.95 at all sites. This value is about what is predicted by a simple Beers Law conversion of LAI to FPAR (Table 1). The Beer's Law conversion does not take into account clumping of foliage which is common in conifer stands and would tend to reduce FPAR (Stenberg 1996). The MODIS FPARs thus appear to be overestimates at MR and NR. Interestingly, the  $SW_{fill}$  FPARs exhibit more dynamic range between sites than the MODIS $_{fill}$  product but appear to be underestimates for the most part.

When parameter optimization was run across all sites and years for each FPAR type, the RMSE for GPP and the RMSE for  $R_e$  were lowest for MODIS $_{TS}$  and RMSE for NEE was lowest for  $SW_{fill}$  (Table 2). In the one-to-one plot for NEE, the slope and the  $R^2$  values were similar for MODIS $_{fill}$  and MODIS $_{TS}$  but the slope was closer to 1.0 and the  $R^2$  higher for  $SW_{fill}$  (Figure 3).

The differences in FPAR resulted in different values for the optimized parameters in some cases (data not shown). The modest benefits of the greater dynamic range across sites in  $SW_{fill}$  were most evident at the NR site (Figure 4). At that subalpine site, the flux rates were generally low relative to the other sites, so in a multisite optimization its estimates for GPP and  $R_e$  tended to be high. This was much more the case with the MODIS $_{fill}$  product because there was essentially no difference in the FPARs. With  $SW_{fill}$ , the lower absolute FPAR at the NR site helped bring the simulated fluxes down. As would be expected, the optimized base rates were generally lower for the MODIS FPARs compared to the SW FPARs because the MODIS FPARs were consistently higher.

## Site-level Optimization

### *Gross Primary Production*

In the observations, it is clear that available  $\downarrow PAR$  tends to be the dominant influence on GPP in these coniferous forests. Day-to-day variation is smallest at CR (Figure 5) which also has the mildest winter and summertime temperatures. Much larger day-to-day variation in GPP is found at the other sites and appears to be driven primarily by episodes of high VPD during the main part of the growing season and low temperatures in the winter. There is evidence of soil drought effects on GPP at MR and WR in some years.

The optimization “chose” to use the VPD scalar at all sites and it was obviously helping drive down simulated GPP on high VPD days in parallel with the observations. The optimizations also chose to use the Tmin scalar except at WR and it was obviously helping capture day-to-day variation in GPP during the winter. A significant proportion of annual GPP occurs during the winter at WR (Falk et al. 2008) which suggests little sensitivity to temperature per se. Whereas the observed clear-sky LUE varied by a factor of 3 (Table 1), optimized values for the maximum LUE ranged between 3.0 (NR) and 4.0 (MR) (Table 3).

### *Ecosystem Respiration*

Tower observations of  $R_e$  showed a similar seasonality to GPP (Figure 6). The day-to-day variability in  $R_e$  was greater at the 2 high LAI sites, probably because of the higher foliar biomass and the sensitivity of foliar respiration to air temperature. Day-to-day variation was lowest at the coolest site (NR).

The simulations captured much of the mid-growing season day-to-day variability at CR and WR (Figure 6). At MR the  $R_h$  was shut down by the soil moisture scalar in years with dry summers, which appeared to match observations.

The optimal base rates for maintenance respiration varied by over a factor of 4 whereas the selected base rate for  $R_h$ , and the  $\alpha$  parameter for  $R_h$ , varied by a factor of 2 to 4 (Table 3).

### *Net Ecosystem Exchange*

At all sites, there is a period of positive NEE (carbon sink) in the spring and early summer followed by a sustained or fluctuating period of negative NEE (carbon source) in mid summer (Figure 7). This patterns is most apparent at WR and least so at NR. Day-to-day variation in NEE is high at all sites. The simulations generally followed the seasonal trend seen in the observations and showed day-to-day variation of similar magnitude and response to environmental variation.

### *Interannual Variation*

NEE is usually a small difference between the much larger GPP and  $R_e$  fluxes. Thus interannual variation in either GPP or  $R_e$  tends to propagate into NEE. At the annual time step, the tower data and simulations showed a similar amount of interannual variation in GPP,  $R_e$ , and NEE. The sign of the year-to-year changes was generally in agreement between tower and modeled data (Figure 8).

Tower and model data generally showed that monthly  $R_e$  anomalies that were correlated with monthly GPP anomalies (Table 4). Soil drought would tend to affect GPP and  $R_e$  similarly, which would explain that general correlation. Cool temperatures would likely reduce  $R_e$  but not necessarily GPP, which would tend to weaken the correlation of the GPP and  $R_e$  anomalies. NEE monthly anomalies were strongly correlated with GPP anomalies at the ME and NR sites in both tower and model data. In contrast, the NEE anomalies were most correlated with the  $R_e$  anomalies at WR and CR in the tower data. There was only weak correlation of NEE anomalies with  $R_e$  anomalies in the model data.

### **Cross-site and Off-site Parameter Optimization**

In the cross-site optimizations, the parameter values selected were generally intermediate among the ranges of site specific values (Table 3). The ability of the site-level simulations to capture variation was generally reduced in the case of the multisite optimization. RMSE always increased in the case of GPP through not always for NEE

(Table 5). The ability to capture interannual variation in NEE was also reduced (Figure 9).

When parameters from the WR optimization were used at the other sites, the mid growing season residuals generally increased relative to the site level parameterization (Figure 10). In the case of GPP at MR, the more positive residuals (model underestimates) were primarily because of the greater sensitivity to VPD at WR (Table 3) and relatively high VPDs elsewhere, especially at MR. In the case of  $R_h$ , the higher residuals were primarily because of the relatively low sensitivity of  $R_h$  to temperature at WR (Table 3) which tended to cause underestimates elsewhere.

The cross-site, cross-year RMSEs for GPP were similar in each case where the site specific parameter values were used across all sites. The RMSEs for  $R_e$  varied more widely (1.33 – 2.36) (Figure 11).

## **Discussion**

### **FPAR Issues**

Both the MODIS and SeaWiFS FPAR products are based on surface reflectance data and radiative transfer modeling (Myneni et al. 2002, Gobron et al. 2006). Despite an 8-10 day compositing period, many bin periods remained at these sites that were continuously overcast at the overpass time (12:00 for MODIS and 13:30 for SeaWiFS, local time). Once the intervals with low quality data were filled with the Zhao et al algorithm (2005), a mostly stable FPAR trajectory was produced. The MODIS<sub>TS</sub> smoothing clearly reduces some artifactual short term variation in the MODIS<sub>fill</sub> product. The week-to-week variation remaining after filling/smoothing is especially low in the summer growing season when FPAR is most important.

The absolute magnitude of the FPAR estimates was consistently high for the MODIS products, with summertime FPARs on the order of 0.95 across all sites. These high FPARs are accurate at the two high LAI sites (CR and WR) but are clearly overestimates at MR and NR where LAIs are much lower. A tendency for the MODIS product to overestimate FPAR has also been observed in other biomes (Fensholt et al. 2004, Turner et al. 2005). These results imply that the MODIS algorithm may be oversensitive at low FPARs and tend to saturate at high FPARs. The Enhanced Vegetation Index (EVI) is also produced from the MODIS reflectances and was designed to address the saturation issue (Huete et al. 2002). EVI is used as a substitute for FPAR in several diagnostic carbon flux models (Xiao et al. 2004, Sims et al. 2005) but the saturation issue has not been examined.

The SeaWiFS FPARs had maximum values of about 0.6 at CR and WR, which were clearly underestimates. Maximum values at MR and NR were about 0.3 which were also consistent underestimates. However, there appears to be more information on spatial patterns in FPAR in the SeaWiFS product at these conifer forest sites compared to the MODIS product because of the greater dynamic range between low and high FPAR sites.

At the NR site, there are periods of snow cover every year and these seem to be registered on the MODIS product but not the SW product. In contrast, snow is rare at the CR site. Nevertheless, both FPAR products there show seasonality in FPAR, probably related to issues with cloudiness. In any case, the apparent FPAR artifacts during the winter at these sites have little effect on simulated fluxes because incident PAR and  $T_{min}$  are relatively low already.

For the most part, FPAR does not vary much interannually at conifer sites ( ), which is consistent with the similar satellite-based estimates for midsummer FPARs across years at these sites. Both the MODIS and SeaWiFS products have been shown to be sensitive to large disturbances such as fire (Turner et al. 2006, Gobron et al. 2006).

The slightly more accurate simulations of NEE using  $SW_{fill}$  for the cross site optimization (Table 2, Figure 3) would be expected because the lower FPARs in  $SW_{fill}$  at the less productive sites is providing the simulation with more information than is the case with  $MODIS_{fill}$ . The difference between outputs based on  $MODIS_{fill}$  and  $SW_{fill}$  is greatest at the low LAI sites like NR (Figure 4). The artifactually high FPAR in  $MODIS_{fill}$  tends to push the GPP and  $R_e$  too high there. The optimized based rates for  $R_a$  and  $R_h$  were high in the case of the  $SW_{fill}$  optimization (Table 2) because both  $R_a$  and  $R_h$  are driven by FPAR and since the FPARs are low, the optimized base rates are high.

The RMSEs for the  $MODIS_{TS}$  FPAR were less than or equal to those for the  $MODIS_{fill}$  FPAR. The modest benefits are a function of smoothing out artifactual short term variation associated with clouds. Nightengale et al. ( In Press) showed a similar modest effect of the Timesat smoothing when the product was used in CASA, another diagnostic carbon flux model.

### **Variation in Site-Level Parameterization**

The sites differed widely in the maximum and average values for GPP. The maximum values for tower GPP were greatest at CR, intermediate at WR and MR, and lowest at NR. These values are consistent with expectations based on climate and stand age: NR is the coldest site and the low maximum GPP is associated with a conservative ecophysiological strategy often found in trees in extreme environments (Woodward 1995). The stand age at NR is also relatively high which introduces an additional constraint on productivity (Gower et al. 1996). CR has a mild climate and is a relatively young stand, thus has higher maximum GPP. The WR site is unusual in having relatively old trees (~ 450 yrs), which may account for the lower maximum GPP. The MR site is young for Ponderosa pine but often experiences effects of high VPDs and soil drought on GPP.

With site-level optimization, the CFLUX simulations of GPP generally agreed well with the tower data. One exception was a period of high GPP in the simulations at NR in 2004 driven by an artifactual bump in the FPAR (Figure 2, 5). A second exception was the days of artificially low GPP in mid summer at WR. The optimization there selected VPD

limits of 0 and 2500 Pa, which were low relative to the limits selected at the other sites and tended to make the simulations over sensitive to VPD.

As would be expected because of its low productivity, the observed clear-sky LUE (Table 1) and optimize maximum LUE (Table 3) were lowest at NR among the sites. Values for maximum LUE ranged from 3 to 4 gC/MJ at the other sites, close to the maximum physiologically possible LUE.

The optimized values for minimum temperature parameters were similar across sites and were similar to the values used in the MOD17 diagnostic model in global runs with MODIS data (Running et al. 2000). The optimization did not use the  $T_{min}$  scalar at WR, possibly because incident PAR was a better predictor. The optimization selected a relatively low VPD minimum and maximum at WR and this may reflect a conservative ecophysiology associated with the quite old trees there.

The maximum  $R_e$  in the observations generally followed the pattern in maximum GPP, with  $CR > WR > MR > NR$ . After optimizing the base rates for  $R_m$  and  $R_h$ , the simulations showed generally good agreement with the observations. The optimized values for the base rate of  $R_m$  were conspicuously low at CR (Table 3) which is consistent with it being a relatively young stand in a favorable site. The optimized base rate for  $R_h$  was also relatively low at CR but the temperature sensitivity for  $R_h$  was much higher than at the other sites, thus apparently compensating for the lower base rate.

The observations showed strong site-specific differences in the relative importance of GPP vs.  $R_e$  monthly anomalies in explaining NEE monthly anomalies. At MR and NR, the GPP anomaly was more closely correlated with the NEE anomaly whereas at CR and WR it was the  $R_e$  anomaly. This difference could be interpreted as a greater sensitivity of  $R_m$  component of  $R_e$  at CR and WR because LAI and aboveground biomass were much greater (Fauk et al. 2008). The modeled NEE anomalies were most strongly driven by GPP anomalies in all cases. The difference at the high LAI sites may be due to an underestimation of  $R_m$  because the values of SeaWiFS FPARs are artifactually low. Nevertheless, the model did account for 70% of the year to year variation in NEE across all sites (Figure 9).

### **Cross-site Parameter Optimization**

The increase in error when running with parameters optimized across all sites is expected because parameters optimized at the site level differed from those derived from the cross site optimization in some cases. The RMSE increase was less than 25% except in one case (NEE at NR). There were much larger increases in error in some cases when parameters optimized at one site were used across all sites (Figure 11). The cross-site RMSE for NEE was between 1.26 and 1.75 with the site-specific optimization and was 1.13 with the cross-site optimization. This response indicates the benefits of a multisite parameter optimization approach.

With the increase in number of flux towers either currently or previously supported in each biome, the possibilities for alternative parameter optimization schemes is growing. Two or more tower sites can be found in most of the Level I ecoregions in North America (CEC 2008). Further research is needed on the possible trade-offs of using a single tower site in a Level II or Level III ecoregion vs. multiple towers sites in a Level I ecoregion. In Turner et al. (2006), CFLUX was optimized by vegetation cover type for the Level 3 ecoregions in western Oregon but that required using outputs from the Biome-BGC model run at selected points as reference data because there were insufficient towers. Either multiple sites within Level I ecoregions or single sites within higher level ecoregion stratifications would be an improvement over single site per ecoregion at a low level of ecoregion stratification.

## Conclusions

Diagnostic carbon cycle models are increasingly used to monitor terrestrial gross ecosystem exchange, ecosystem respiration, and net ecosystem exchange at regional to global scales. FPAR products from different sensors vary widely in their absolute values for particular sites and their dynamic range across sites. Site-specific parameter optimization at eddy covariance flux tower sites can produce simulations with good fits to observational data but optimized parameters may vary across sites within a biome. For large area simulations, a cross-site parameter optimization within a given vegetation cover type will reduce prediction error compared with a single site optimization.

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Table 1. Site characteristics.  $LUE_{\text{clear-sky}}$  refers to light use efficiency at the flux tower under clear skies and favorable conditions.

Site	Campbell River <sup>a</sup>	Wind River <sup>b</sup>	Metolius River <sup>c</sup>	Niwot Ridge <sup>d</sup>
Location	49°52'N, 125°20'W	45°49'N 121°57'W	44°27'N 121°33'W	40°02'N 105°33'W
Precipitation (cm)	1500	247	55	80
Mean Annual Temperature (°C)	8.5	8.7	7.5	1.5
Stand Age (yrs)	56	~ 450	89	~ 100
Leaf Area Index (m <sup>2</sup> m <sup>-2</sup> )	8.4	8.6	2.8	4.2
fPAR (0-1)	0.95 <sup>e</sup>	0.95 <sup>e</sup>	0.45 <sup>f</sup>	0.93 <sup>e</sup>
$LUE_{\text{clear-sky}}$ (gC MJ <sup>-1</sup> )	1.0	1.2	0.9	0.4

<sup>a</sup> Humphreys et al. 2006

<sup>b</sup> Falk et al. 2008

<sup>c</sup> Irvine et al. 2004

<sup>d</sup> Sacks et al. 2007

<sup>e</sup> Derived from LAI using Beer's Law (Jarvis and Levarez 1983)

<sup>f</sup> Makela et al. 2008

Table 2. Comparison of RMSE for gross ecosystem exchange (GEE), ecosystem respiration ( $R_e$ ) and net ecosystem exchange (NEE) for three forms of FPAR. Parameter optimization was across all sites and all years.

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Error	FPAR Type		
	MODIS <sub>fill</sub>	MODIS <sub>TS</sub>	SeaWiFS <sub>fill</sub>
RMSE <sub>GPP</sub>	1.68	1.55	1.67
RMSE <sub>Re</sub>	1.54	1.43	1.45
RMSE <sub>NEE</sub>	1.25	1.26	1.13

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Table 3. Ecophysiological parameter estimates for site-specific and cross-site optimizations. LUE is light use efficiency. Tmin\_min is the temperature at which LUE begins to be reduced. Tmin\_max is the temperature at which LUE is reduced to zero. VPD\_min is the vapor pressure deficit at which LUE begins to be reduced. VPD\_max is the vapor pressure deficit at which LUE is reduced to zero. Rm\_base is the base rate for maintenance respiration. Rh\_base is the base rate for heterotrophic respiration. Rh\_a is the temperature sensitivity coefficient. FPAR\_min is the minimum value for FPAR in the Rh algorithm.

	Site				
	CR	WR	ME	NR	Cross-site
<b>Parameter</b>					
LUE_max (gC MJ <sup>-1</sup> )	4.0	3.5	4.0	3.0	4.0
Tmin_min (°C)	-12	NO <sup>1</sup>	-12	-8	-12
Tmin_max (°C)	4	NO <sup>1</sup>	6	4	4
VPD_min (Pa)	1000	0	1000	1000	0
VPD_max (Pa)	4000	2500	4000	3000	3500
Rm_base (gC m <sup>-2</sup> d <sup>-1</sup> )	0.7	2.7	2.3	2.9	0.8
Rh_base (gC m <sup>-2</sup> d <sup>-1</sup> )	5.0	5.8	10.0	10.0	8.8
Rh_a (unitless)	0.18	0.05	0.09	0.05	0.10
FPAR_min (0-1)	0.30	0.80	0.50	0.60	0.40

<sup>1</sup>NO = Not Optimized

Table 4. Relationships of monthly anomalies (anom) for gross primary production (GPP), ecosystem respiration (Re), and net ecosystem exchange (NEE). FPAR type is SW<sub>fill</sub> and optimization type is site-specific.

Site	Tower		Model	
	Best Fit	R <sup>2</sup>	Best Fit	R <sup>2</sup>
NEP anom vs. GPP anom				
CR	$y = -0.11x - 0.01$	0.01	$y = 0.43x + 0.01$	0.26
WR	$y = 0.30x + 0.00$	0.05	$y = 0.62x + 0.00$	0.82
ME	$y = 0.59x + 0.01$	0.82	$y = 0.51x - 0.01$	0.77
NR	$y = 0.59x + 0.01$	0.63	$y = 0.54x - 0.01$	0.66
NEP anom vs. Re anom				
CR	$y = -0.57x - 0.01$	0.62	$y = -0.34x + 0.00$	0.13
WR	$y = -0.70x + 0.00$	0.59	$y = 0.65x - 0.00$	0.21
ME	$y = 0.70x + 0.01$	0.28	$y = 0.55x + 0.01$	0.28
NR	$y = 0.09x + 0.00$	0.00	$y = 0.26x - 0.01$	0.05
GPP anom vs. Re anom				
CR	$y = 0.43x - 0.00$	0.48	$y = 0.66x - 0.00$	0.38
WR	$y = 0.30x - 0.01$	0.21	$y = 1.66x - 0.01$	0.63
ME	$y = 1.70x - 0.00$	0.70	$y = 1.55x - 0.01$	0.76
NR	$y = 1.01x - 0.01$	0.44	$y = 1.26x - 0.01$	0.58

Table 5. Root Mean Square Error (RMSE) at the site level for gross primary production (GPP), ecosystem respiration ( $R_e$ ) and net ecosystem exchange (NEE) using site-specific and cross-site parameter optimization.

		Site			
		CR	WR	ME	NR
GPP	RMSE <sub>site</sub>	1.48	1.69	1.21	0.68
	RMSE <sub>cross-site</sub>	1.90	2.15	1.50	0.77
Re	RMSE <sub>site</sub>	1.30	1.69	1.21	0.68
	RMSE <sub>cross-site</sub>	2.13	1.58	1.07	0.50
NEE	RMSE <sub>site</sub>	1.18	1.40	1.00	0.52
	RMSE <sub>cross-site</sub>	1.19	1.46	0.99	0.72

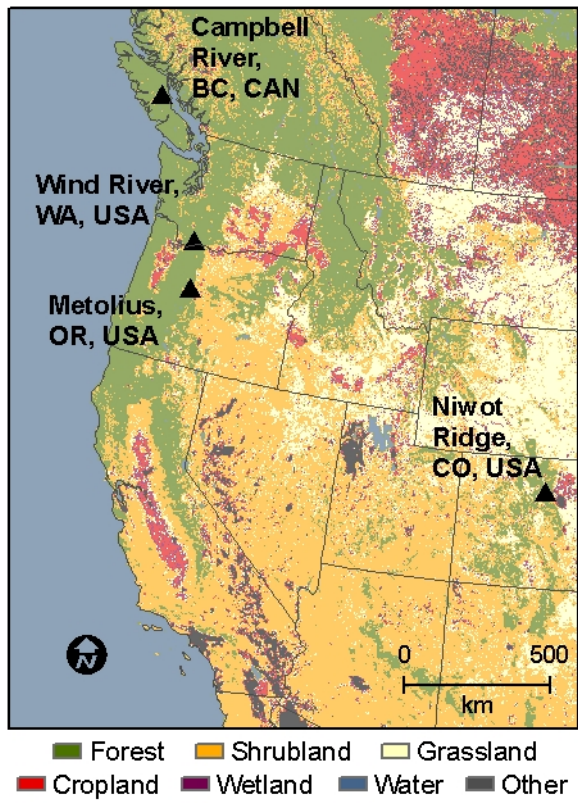


Figure 1. Site locations. Background vegetation cover is from the MODIS sensor.



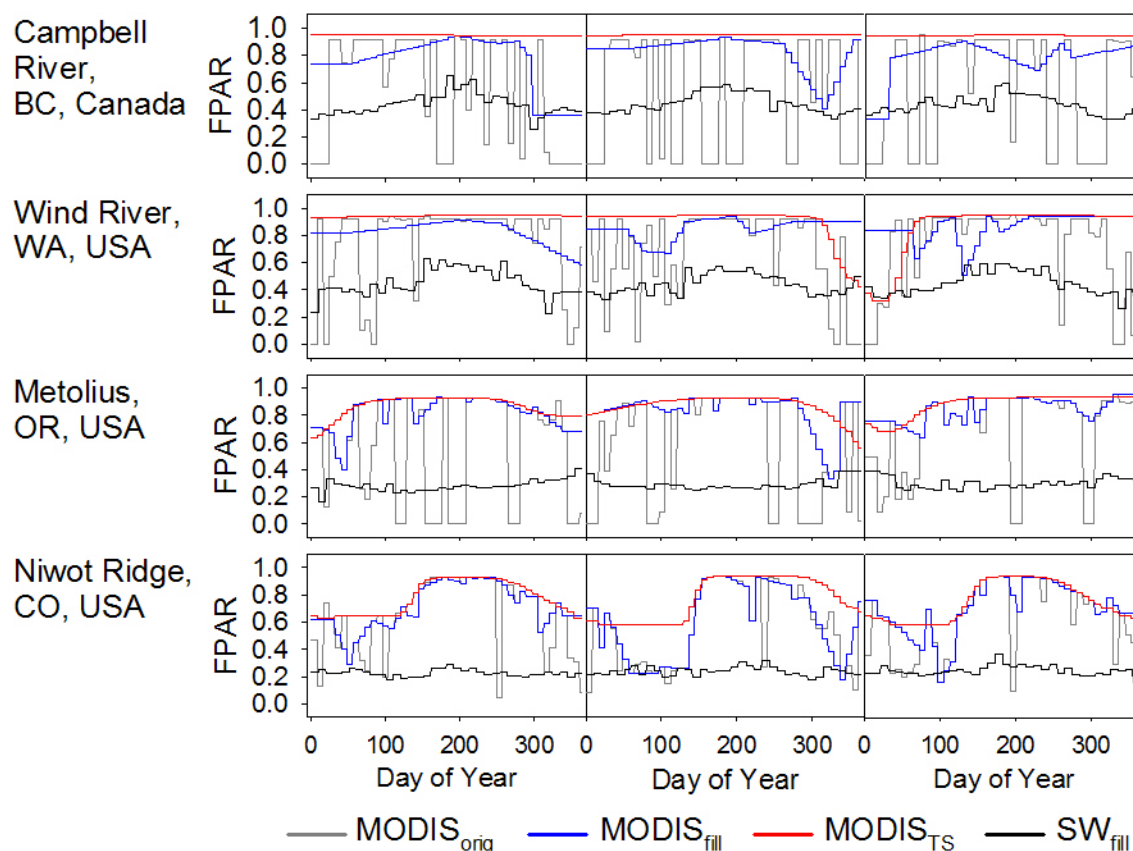


Figure 2. Four versions of FPAR time series data.  $MODIS_{orig}$  is the standard product as it comes from NASA.  $MODIS_{fill}$  is the same data with missing dates filled in using the Zhao et al. (2005) algorithm.  $MODIS_{ts}$  is the  $MODIS_{fill}$  data smoothed with the TIMESAT algorithm (Jonsson and Eklund 2004).  $SW_{fill}$  is the FPAR product from the SeaWiFS sensor (Gobron et al. 2006) filled using the Zhao et al. (2005) algorithm. Years are 2002-2004 except CR (2001-2003).

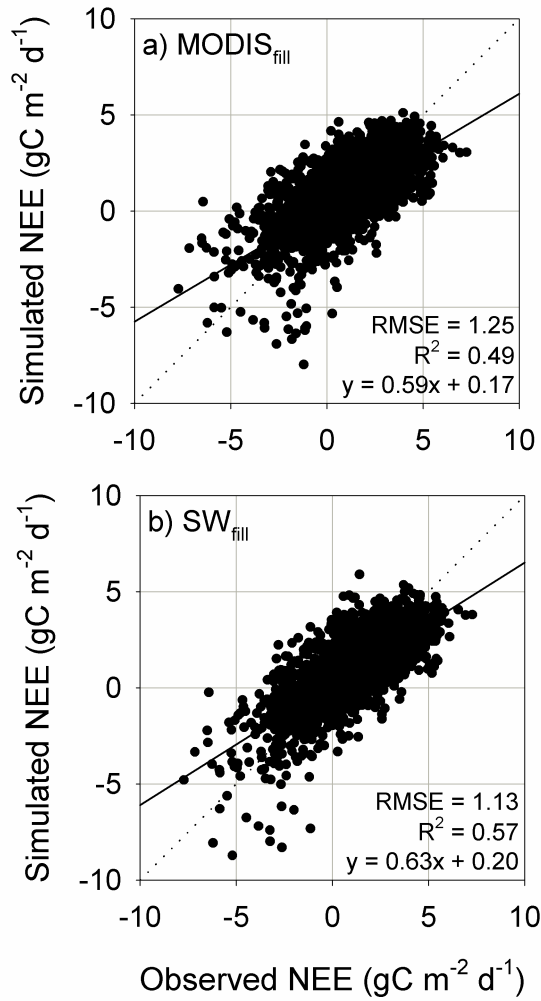


Figure 3. Comparison of scatter plots of net ecosystem exchange (NEE) for the MODIS<sub>fill</sub> and SW<sub>fill</sub> FPAR products across all sites and years. Separate parameter optimizations (one optimization across all sites + all years) were run for each FPAR product.

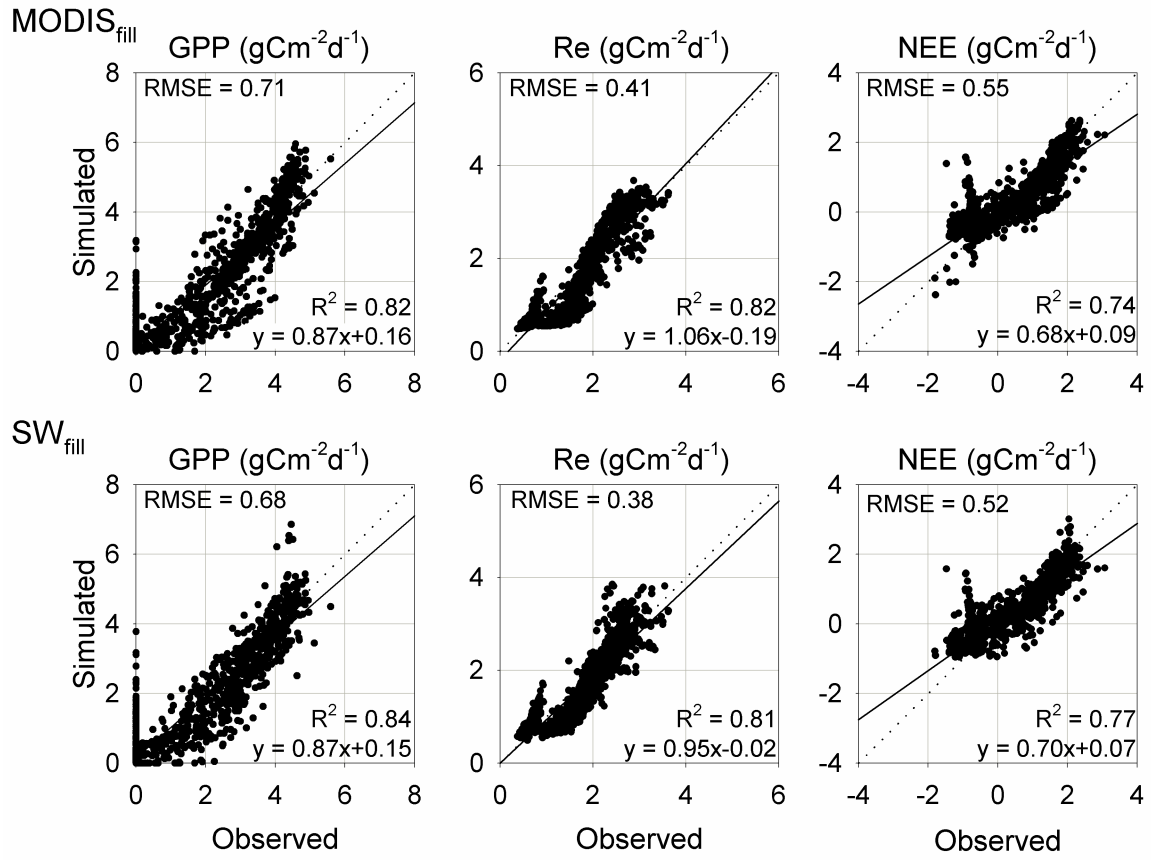


Figure 4. Comparison of scatter plots for gross primary production (GPP), ecosystem respiration ( $R_e$ ), and net ecosystem exchange (NEE) using MODIS<sub>fill</sub> and SW<sub>fill</sub> at the Niwot Ridge site. A site-specific parameter optimization was used.

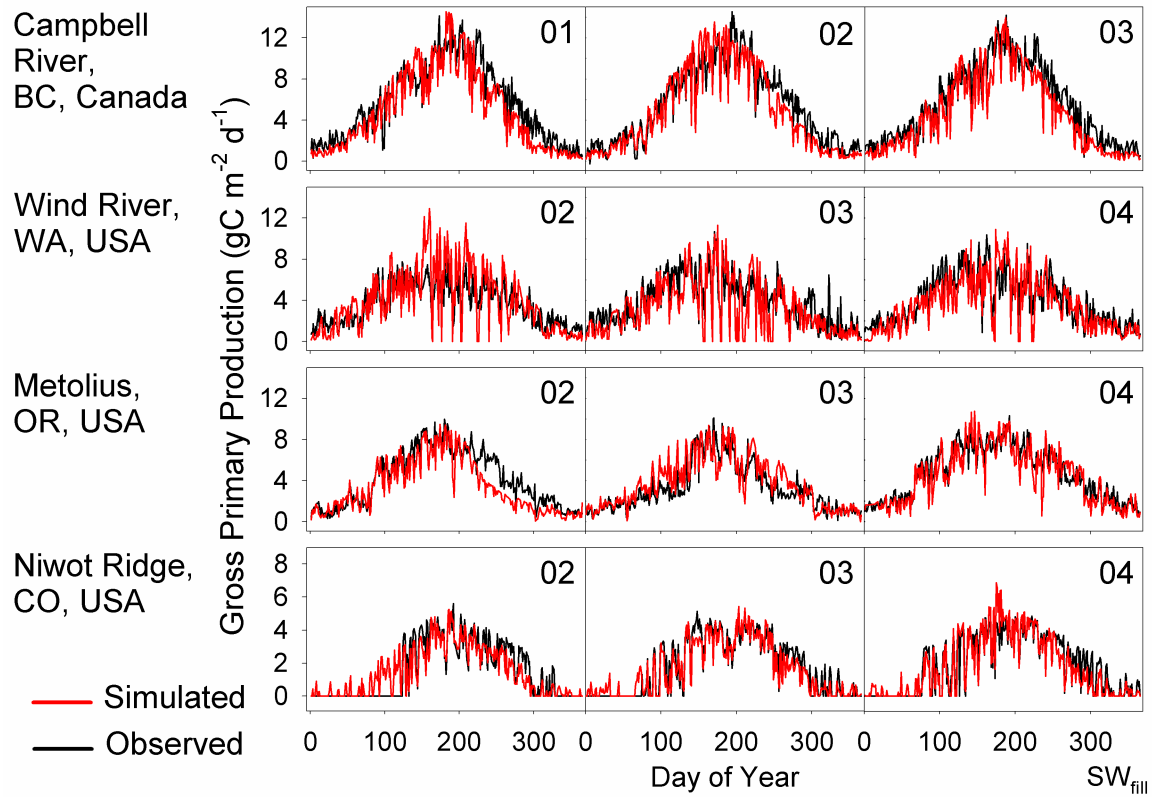


Figure 5. Times series comparison of observed and simulated gross primary production. The  $SW_{fill}$  FPAR product and site level optimizations were used. The numbers in the upper right corner of each panel refer to the year.

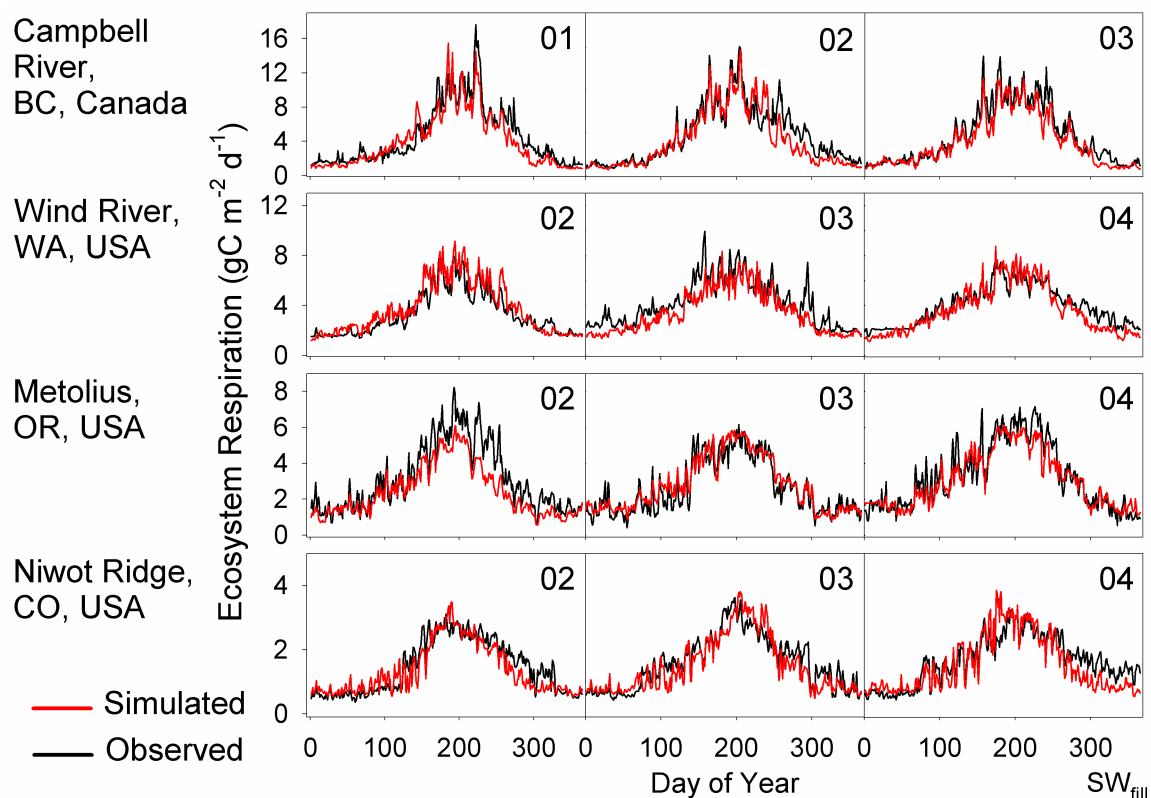


Figure 6. Times series comparison of observed and simulated ecosystem respiration. The  $\text{SW}_{\text{fill}}$  FPAR product and site level optimizations were used. The numbers in the upper right corner of each panel refer to the year.

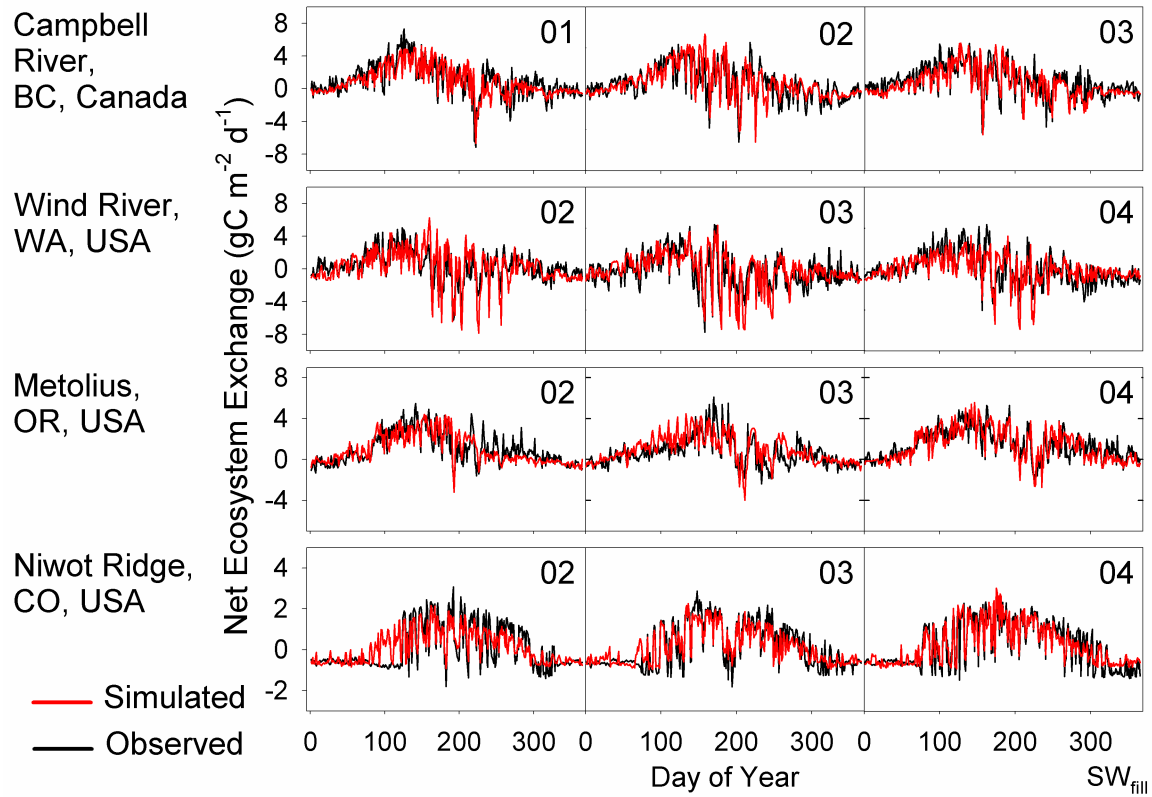


Figure 7. Time series comparison of observed and simulated net ecosystem exchange. The  $\text{SW}_{\text{fill}}$  FPAR product and site level optimizations were used. The numbers in the upper right corner of each panel refer to the year.

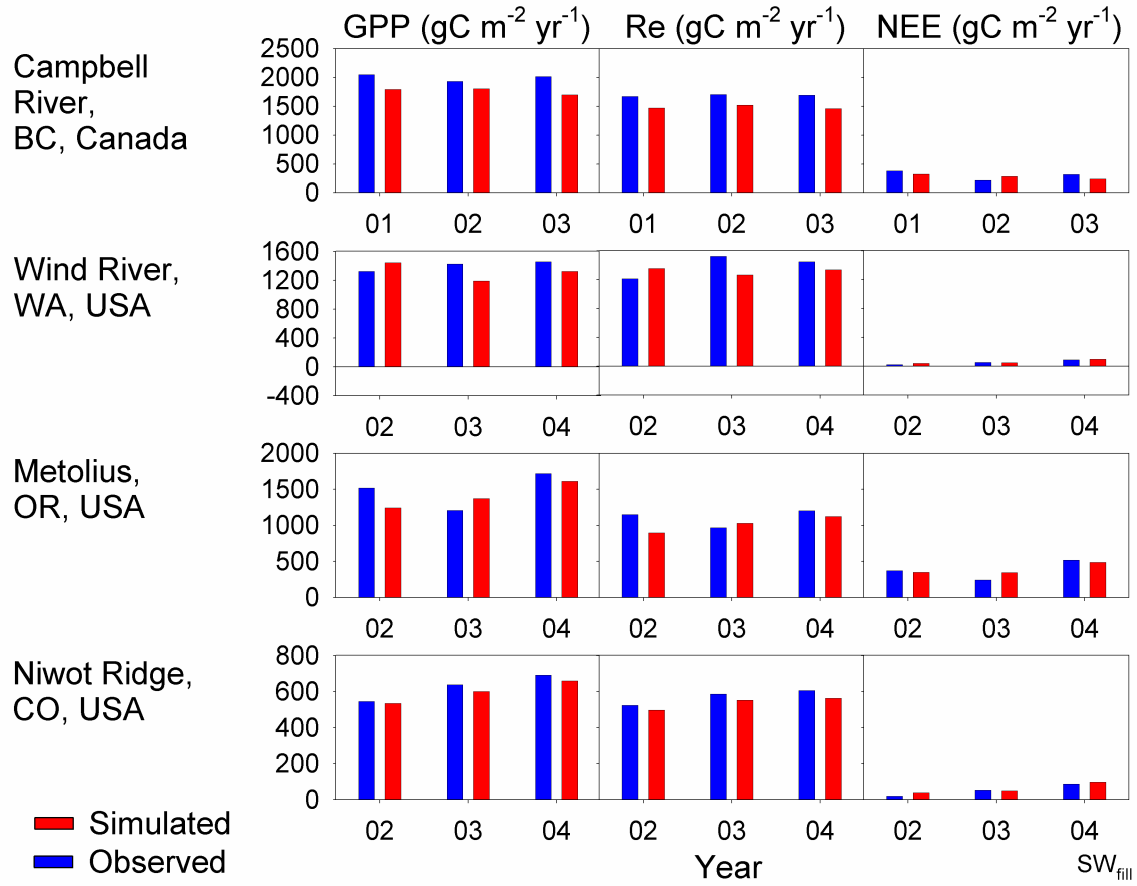


Figure 8. Interannual variation in gross primary production (GPP), ecosystem respiration ( $R_e$ ), and net ecosystem exchange (NEE) for tower observations and model simulations. The  $SW_{fill}$  FPAR and site level optimizations were used.

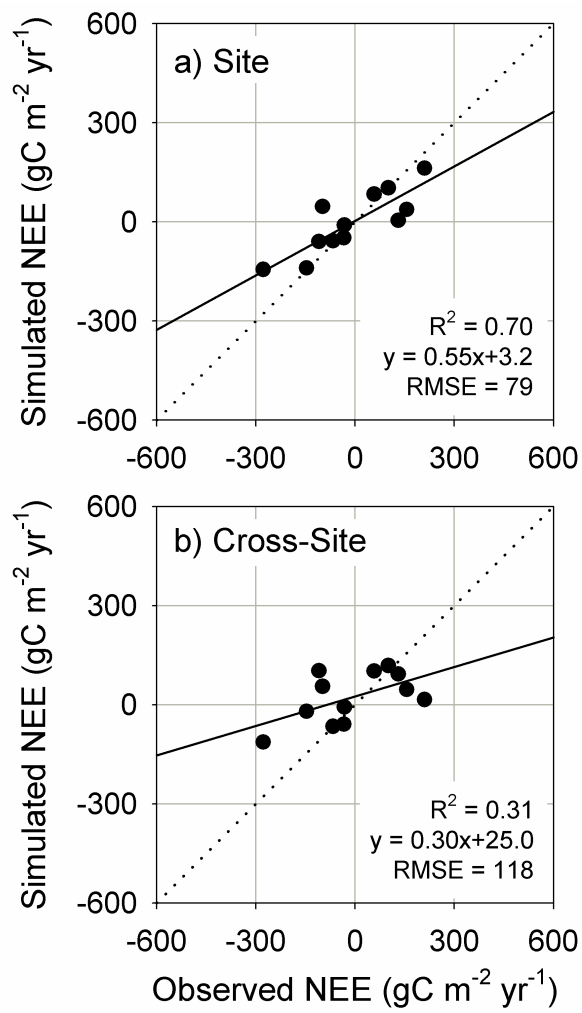


Figure 9. Relationship of the sign and magnitude of year-to-year differences in NEE using a) site-level parameter optimizations and b) a cross-site optimization. Each point represents one year-to-year difference at one site.



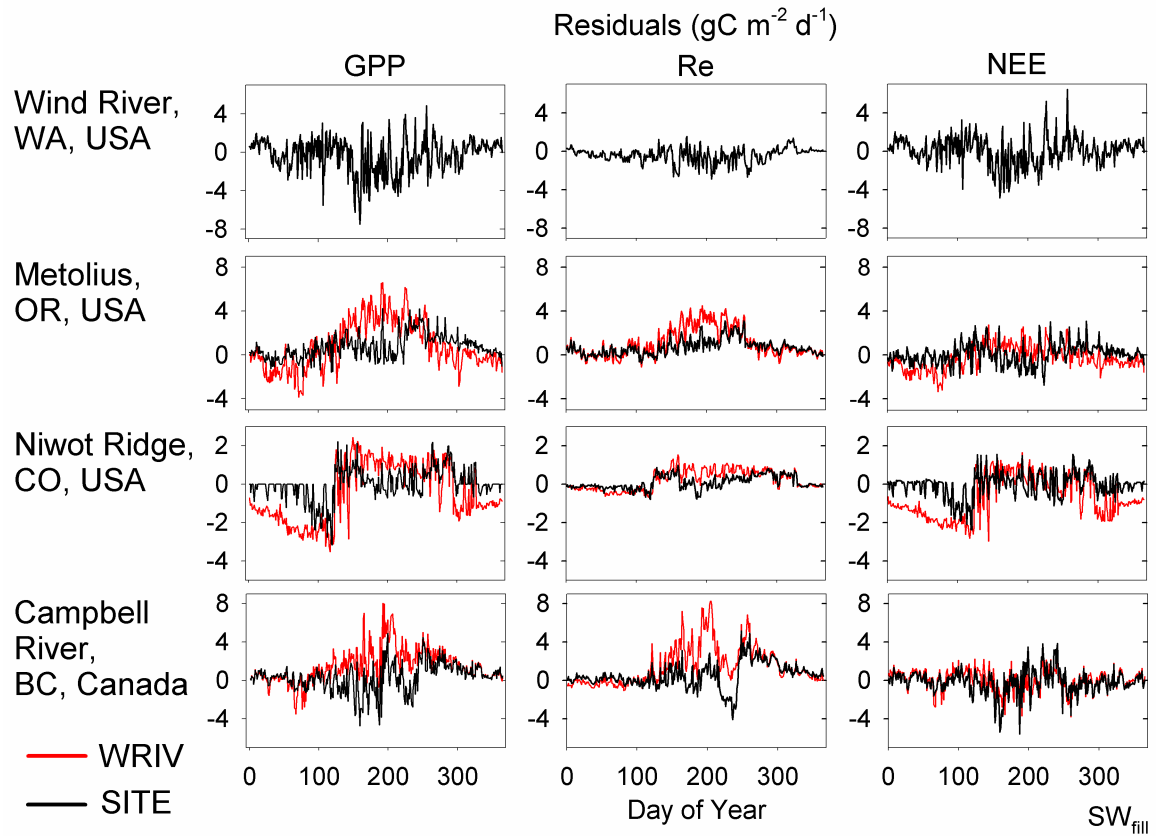


Figure 10. Time series for the residuals for gross primary production (GPP), ecosystem respiration (Re), and net ecosystem exchange (NEE). The year is 2002. Each panel has the residual (model – tower) for its site optimization and the residual when run with the Wind River site optimization parameters.

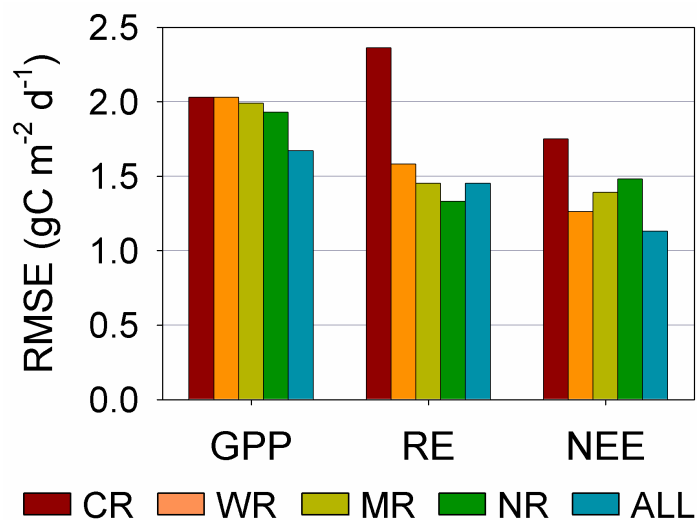


Figure 11. Effect on cross-site Root Mean Square Error (RMSE) of using site-specific parameters when running across sites. CR = Campbell River, WR = Wind River, MR = Metolius River, NR = Niwot Ridge, All = cross-site.